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Control of proton exchange membrane fuel cell system breathing based on maximum net power control strategy

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HIGHLIGHTS

- Analysis for maximum net power characterization of PEMFC system is carried out.
- A MNPC strategy based on IGPC and a reference governor is proposed.
- The IGPC based on EIA-PSO is developed to solve the predictive control law.
- The results demonstrate that the proposed strategy has better robust performance.

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ABSTRACT

In order to achieve the maximum net power, the analysis for the maximum net power characterization of a proton exchange membrane fuel cell (PEMFC) system is carried out. A maximum net power control (MNPC) strategy based on an implicit generalized predictive control (IGPC) and a reference governor is proposed to keep optimal oxygen excess ratio (OER) trajectory. The IGPC based on an effective informed adaptive particle swarm optimization (EIA-PSO) algorithm is developed to solve the predictive control law and reduce the computational complexity in the rolling optimization process. The simulations of three conditional tests are implemented and the results demonstrate that the proposed strategy can track the optimal OER trajectory, reduce the parasitic power and maximize the output net power. The comprehensive comparisons based on three conditional tests verify that the MNPC–IGPC has better robust performance in the presence of large disturbances, time delay and various noises. The experimental comparison with internal control system of Ballard 1.2 kW Nexa Power Module testifies the validity of the MNPC–IGPC for increasing the net power. Hence, this proposed strategy can provide better behavior to guarantee optimal OER trajectory and the maximum net power even though the disturbances and uncertainties occur.

1. Introduction

Fuel cells that convert chemical energy of the fuel into electricity without combustion are studied worldwide. Due to its high efficiency, low operating temperature and low pollution, a proton exchange membrane fuel cell (PEMFC) is considered as one of the most promising technologies for a wide range of applications [1–3]. The PEMFC is generally viewed as a dependable power source, such as distributed power generation, automobile and portable power source [4–7].

A PEMFC system is a strongly coupled, nonlinear, complex system. The stack current changes when the droved load changes. Simultaneously, the electrochemistry reaction is accelerated corresponding to the variation. If the flow rate of oxygen in cathode is too low, the output power of PEMFC system could be decreased because of lacking oxygen, which is so-called starvation. However, excess oxygen replenishment into the cathode will cause power waste, consequently leading to a decrease in the net power of overall system. Several studies have addressed these undesired phenomenon, proposing that the oxygen excess ratio (OER) should be controlled to prevent oxygen starvation and excess oxygen replenishment [8–10]. For the PEMFC system considered in this paper, the air supply subsystem has slower dynamics compared with the hydrogen supply subsystem, hence the oxygen starvation and excess oxygen replenishment are the more obstinate problems during fast transient operation, such as accelerated and decelerated process of electrical vehicle [9,10]. Hence, it is so significant to

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utilize an effective control strategy to maintain optimal OER for the maximization of net output power of PEMFC system.

A variety of control strategies have been used to PEMFC system during recent years. Pukrushpan et al. [10] have designed feedforward and feedback strategies to control the voltage of compressor in a PEMFC air supply system. The desired OER is set to a constant value for starvation prevention, neglecting the optimal OER trajectory. Schumacher et al. [11] have proposed a water management method of PEMFC using fuzzy control. Jing Sun et al. [12] have proposed a robust nonlinear reference governor approach for fuel cell oxygen starvation. According to the experimental data, Almeda et al. [13] have utilized artificial neural network to control output voltage and optimize the parameters of fuel cell system. Woon Ki Na et al. [14] have presented a nonlinear pressure controller based on a nonlinear PEMFC model to prolong the stack life. Qi Li et al. [15] have used state feedback exact linearization to design a nonlinear H_∞ optimal controller for minimizing the pressure deviations between the anode and cathode of PEMFC. Alicia Arce et al. [16] have reported a control architecture based on a constrained explicit model predictive control (MPC) law suitable for real time implementation. Winston et al. [17] have proposed and tested the regulation of OER on a real fuel cell using sliding mode control (SMC) theory. However, in these works the proposed control strategies had not adequately considered the influence of uncertainty and disturbance, such as neglected variations of system parameters due to environmental change, time delay and nonlinearities of PEMFC system.

Generalized Predictive Control (GPC) developed by Clarke et al. [18,19] have been widely applied in the process industry due to its capability of obtaining a stable control for systems with varying parameters, time delay, high model order and non-minimum phase. However, the future control-increment vector is derived by recursively solving the Diophantine equation for a given predictive horizon, which is time consuming. Furthermore, many other drawbacks such as complex mathematical derivation and too many tuning parameters are appeared in GPC. In order to reduce the online computation time, a short predictive horizon or a short control horizon is utilized. But this is against the basic principle of the GPC to some extent, which sometimes leads to poor control performance [20,21]. At present, many improved schemes have been proposed to avoid the matrix operation and reduce the computation while keeping a long control horizon at the same time [22–25].

The rolling optimization process is an important part of the GPC, which plays a key role on control effect. Hence it is necessary to seek a highly efficient optimization method. However, this optimization problem is usually very complicated with various constraints. It is difficult to solve this constrained optimization problem by using traditional methods. Currently the intelligence computation technique has attracted attention for the control system design, such as particle swarm optimization (PSO) algorithm which is a swarm intelligence optimization algorithm based on observations of the social behavior of bird flocking [26–29]. In this paper, an effective informed adaptive particle swarm optimization (EIA-PSO) algorithm which was proposed by our team in [30] for improving inherent drawbacks of PSO is utilized to solve the predictive control law in the rolling optimization process.

In this paper, a maximum net power control (MNPC) strategy based on an implicit generalized predictive control (IGPC) and an OER reference governor is proposed for the PEMFC system. The predictive control law which is solved by the EIA-PSO algorithm in the IGPC does not involve the Diophantine equations so that the computational complexity is reduced. The parameters of the output predictive equation are directly identified using the characteristics of the parallel predictors. The control strategy allows a safe and efficient OER control while maximizing the net power of PEMFC system. The simulations of three conditional tests are carried out and the experimental comparison with the commercial Ballard Nexa Power Module internal control system for the maximum net power is also developed.

This paper is organized as follows. Section 2 is dedicated to the maximum net power characterization of PEMFC system. PEMFC net power control algorithm is fully explained in Section 3. Section 4 details results and discussions. Finally, the main conclusions are drawn in Section 5.

2. Maximum net power characterization of PEMFC system

A PEMFC stack needs to be integrated with several auxiliary components to form a complete PEMFC system as Fig. 1 shown. In this paper, a dynamic model of PEMFC system based on [9,10] is utilized by using electrochemical, thermodynamic and fluid mechanics principles. This model of PEMFC prototype is a commercial Ballard 1.2 kW Nexa Power Module which is widely used in vehicle applications. Furthermore, this model describes the thermal system of PEMFC. More details of this PEMFC system model can be found in [9,10].

The majority of the parasitic power for the PEMFC system is spent on the air pump, thus, it is important to determine the proper air flow for maximizing the net power P_{net}. The air flow excess is reflected by OER, defined as the ratio of oxygen supplied $F_{O2,in}$ to oxygen used $F_{O2,ret}$ in the cathode. After an optimum value is reached, however, further increase in OER will result in an increase in pump power so that P_{net} decreases [8–10]. The OER is expressed as follows

$$\mathrm{OER} = \frac{F_{O_2,in}}{F_{O_2,ret}} \tag{1}$$

An experimental testing system consists of a Ballard 1.2 kW Nexa Power Module, an electronic load, and measurement devices installed at School of Electrical Engineering, Southwest Jiaotong University. The Ballard Nexa Power Module is an autonomous commercial system supplying power to the load and all its auxiliary components from its own stack power, composed by an air-cooled stack of 46 cells with internal air humidification and other auxiliary systems. The experimental testing system is setup as shown in Fig. 2. The internal control system of Nexa Power Module has regulation strategy for the air pump voltage that is intended to avoid oxygen starvation.

The analysis of control objectives is shown in Fig. 3, where the behavior of the net power P_{net} as a function of OER in constant net current curves is presented. These net power curves describe the effective power delivered to the load when the demanded net current I_{net} changes from 5A to 35A. The maximum net power

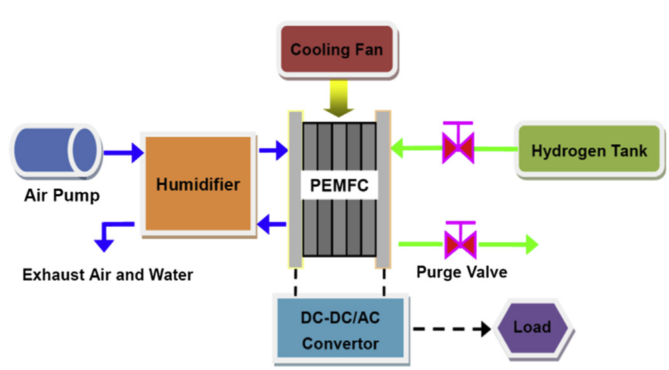

Fig. 1. Schematic diagram of PEMFC system.

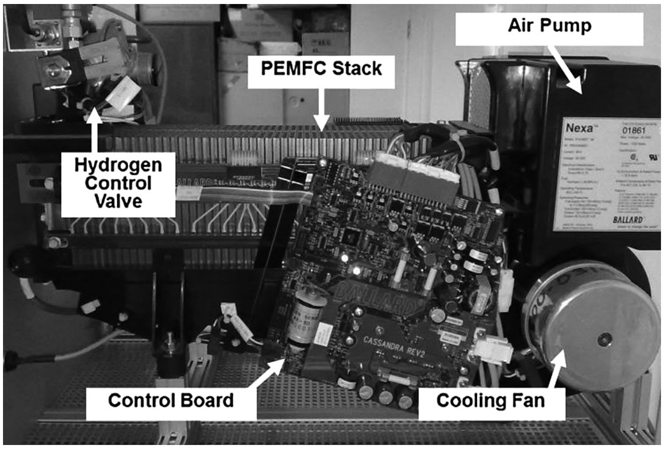

Fig. 2. Experimental testing system.

profile as Fig. 3 shown determines the values of OER. The curve with circle dot is optimal OER trajectory. This paper proposes to follow this optimal OER trajectory in order to supply the maximum net power and smooth behavior of OER.

3. PEMFC net power control algorithm

3.1. Implicit generalized predictive control (IGPC)

The PEMFC system can be described by the controlled auto-regressive integrated moving average (CARIMA) model as follows [18,19]:

$$A\left(z^{-1}\right)y(k) = B\left(z^{-1}\right)u(k-1) + C\left(z^{-1}\right)\frac{\xi(k)}{1-z^{-1}} \tag{2}$$

where $y(k)$, $u(k)$ and $\xi(k)$ are the output, input and noise sequence, respectively; $A(z^{-1})$, $B(z^{-1})$ and $C(z^{-1})$ are polynomials with the backward shift operator z^{-1}.

The best prediction of the output is given by Eq. (2) and Diophantine equation in the vector form

$$\widehat{Y} = G\Delta U + F \tag{3}$$

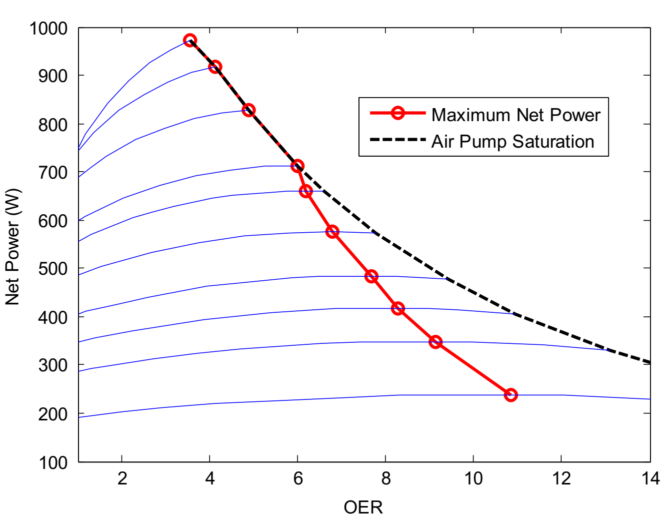

Fig. 3. Maximum net power profile and optimal OER trajectory.

where, the dimension of the vectors are all $n \times 1$:

$$\begin{aligned}
\widehat{Y} &= [\widehat{y}(k+1), \widehat{y}(k+2), \ldots, \widehat{y}(k+n)]^T \\
\Delta U &= [\Delta u(k), \Delta u(k+1), \ldots, \Delta u(k+n-1)]^T \\
F &= [f(k+1), f(k+2), \ldots, f(k+n)]^T
\end{aligned}$$

The matrix G is then lower-triangular of dimension $n \times n$:

$$G = \begin{bmatrix} g_0 & 0 & \cdots & 0 \\ g_1 & g_0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ g_{n-1} & g_{n-2} & \cdots & g_0 \end{bmatrix}$$

In the IGPC, the quadratic cost function is considered

$$J = \sum_{j=1}^{n}[y(k+j) - w(k+j)]^2 + \sum_{j=1}^{m}\lambda[\Delta u(k+j-1)]^2 \tag{4}$$

where n is the maximum prediction horizon, m is the maximum control horizon and λ is a control weighting coefficient. w is softness reference trajectory which is defined as follows

$$w\left(k+j\right) = \alpha^j y\left(k\right) + \left(1-\alpha^j\right)y_r \tag{5}$$

where α is the smoothing factor and y_r is the reference trajectory. And then Eq. (4) can be rewritten in a matrix formulation using the predictive outputs Eq. (3)

$$J = \left(\widehat{Y} - W\right)^T\left(\widehat{Y} - W\right) + \lambda\Delta U^T\Delta U \tag{6}$$

The minimum of J, assuming that there are no constraints on the control signals, can be found by making the gradient of J equal to zero. Then the predictive control law vector ΔU can be obtained as follows

$$\Delta U = \left(G^T G + \lambda I\right)^{-1} G^T(W - F) \tag{7}$$

To obtain the matrix G in the standard adaptive GPC, the Diophantine equation would be computed at first [20,21]. This involves complex matrix computation, which could be prohibitive for some real time applications. For these reasons, it is essential to develop an algorithm which computes the control increment quickly and accurately.

Considering Eq. (3), the last equation can be reformulated as follows

$$y(k+n/k) = X(k)\theta(k) \tag{8}$$

where,

$$\begin{aligned}
X(k) &= [\Delta u(k), \Delta u(k+1), \cdots, \Delta u(k+n-1), 1] \\
\theta\left(k\right) &= [g_{n-1}, g_{n-2}, \ldots, g_0, f(k+n)]^T
\end{aligned}$$

Note that $g_{n-1}, g_{n-2},\ldots,g_0$ are just the elements of the matrix G. It provides a new approach to derive the matrix G without solving the Diophantine equation. In this paper, we propose a new method to derive the matrix G by using the EIA-PSO algorithm.

The open-loop predictive vector F can be derived by the modified method in the IGPC which is utilized the equivalence between the GPC and the dynamic matrix control (DMC). The next time F can be modified as follow

$$F = \begin{bmatrix} f(k+1) \\ f(k+2) \\ \vdots \\ f(k+m) \end{bmatrix} + \begin{bmatrix} m_1 \\ m_2 \\ \vdots \\ m_n \end{bmatrix} [y(k+1) - \hat{y}(k+1)] \tag{9}$$

where, $M = [m_1, m_2, \ldots, m_n]^T$ is the error modified vector.

Note that the IGPC achieves the optimization goal by using the rolling optimization which is different from the optimal control method. In the rolling optimization process of the IGPC, a local optimization goal will be obtained in each prediction horizon rather than using the invariable global optimization goal. Hence, the optimization process is not conducted offline, but is repeated online.

3.2. Solution of predictive control law based on EIA-PSO

The EIA-PSO algorithm is an adaptive swarm intelligence optimization with preferable search ability and search rate based on the equilibrium characteristic between global search and local search. The EIA-PSO includes effective informed strategy, adaptive inertia weight and acceleration coefficient strategies, local search strategy based on BFGS Quasi-Newton method and randomized regrouping strategy. Effective informed strategy proposed improves the PSO algorithm at the aspects of diversity and the balance of exploration and exploitation. According to the idea of division of labor, adaptive inertia weight strategy is introduced and the acceleration coefficients are adjusted adaptively with the variation of inertia weight. In addition, the Broyden–Fletcher–Goldfarb–Shanno (BFGS) Quasi-Newton method is employed to do the local search for increasing the convergence velocity and 5% elitist individuals are chosen to search in local areas after they explore every constant generations (remarked by E generations). Furthermore, in order to avoid the particles easy to converge to a local optimum, the diversity of population is increased in every constant generations (remarked by R generations) by the randomized regrouping strategy. More details of the EIA-PSO algorithm can be found in Ref. [30].

In the effective informed strategy, for increasing the diversity of equilibrium point, the global best position g_i is replaced by the weighted average p_g of the top s particles that are sorted in an ascending order with fitness value. The personal best position p_i is replaced by the weighted average p_a of p_{i-1} and p_i after all particles are also sorted in an ascending order with fitness value. p_g and p_a are expressed as follows

$$p_g = \sum_{j=1}^{s} \mu_j p_j \tag{10}$$

$$\mu_j = \frac{1/F_j}{\sum_{k=1}^{s} \frac{1}{F_k}} \tag{11}$$

$$p_a = \frac{F_i p_{i-1} + F_{i-1} p_i}{F_i + F_{i-1}} \tag{12}$$

where, μ_j is the weighted constant, F_j is the fitness value corresponding particle optimal location.

In the adaptive inertia weight and acceleration coefficient strategy, better balance between the global and local search capabilities can be obtained in per iteration, and it does not require preset maximum iteration. The inertia weight and the corresponding acceleration coefficients of i-th ranked particles are expressed as follows:

$$\xi_i = \xi_{\min} + \frac{(m-i)(\xi_{\max} - \xi_{\min})}{(m-1)} \tag{13}$$

$$\zeta_{i1} = \left(\xi_i + 1 + 2\sqrt{\xi_i}\right) \Big/ 2 \tag{14}$$

$$\zeta_{i2} = \left(\xi_{m+1-i} + 1 + 2\sqrt{\xi_{m+1-i}}\right) \Big/ 2 \tag{15}$$

where, $\xi_{\max}$ and $\xi_{\min}$ are predefined maximum and minimum inertia weights, respectively, and the acceleration coefficients ζ_{i1}, ζ_{i2} adjust adaptively according to ξ_i. Basically, the better particles obtain larger ζ_{i1} and smaller ζ_{i2}, making themselves have better local search ability, and the poor particles obtain smaller ζ_{i1} and larger ζ_{i2}, making themselves have better global search ability.

In this paper, the EIA-PSO algorithm is utilized to solve the predictive control law in the rolling optimization process of the IGPC. Hence, the predictive control law does not involve the Diophantine equations so that the computational complexity is reduced. The parameters of the output predictive equation are directly identified using the characteristics of the parallel predictors. Using the Eq. (4) as the objective function, the implementation procedures are summarized as follows:

Begin
Step 1 $k \leftarrow 1$, set the maximum prediction horizon value and the maximum control horizon value.
Step 2 Obtain the input and output data and initialize EIA-PSO: set the population size, the iteration number, maximum velocity and location boundary, initialize randomly the velocity and position of each particle.
Step 3 Calculate the fitness value of each particle according to Eq. (4), update best location of each particle and their corresponding fitness values.
Step 4 Sort the population in ascending order according to their personal best location.
Step 5 Calculate the inertia weight ξ_i, the corresponding acceleration coefficients ζ_{i1} and ζ_{i2} according to Eq. (13)–(15).
Step 6 Evaluate the personal weighted average best position p_a and the global weighted average best position p_g for each particle according to Eq. (10)–(12).
Step 7 Update each particle's velocity and position.
Step 8 If E generations are satisfied, BFGS Quasi-Newton method is employed to do local search with 5% elitist individuals. Otherwise, go to Step 10.
Step 9 If R generations are satisfied, the population is regrouped randomly and starts searching using a new configuration. Otherwise, go to Step 10.
Step 10 Return the best solution if the stop condition is satisfied. Otherwise, go to Step 3.
Step 11 Derive the matrix G and the predictive control law according to Eq. (7).
Step 12 $k \leftarrow k+1$, control the system by using the predictive control law and go to Step 2 for the rolling optimization.
End

3.3. Design OER reference governor

Contrary to the starvation prevention criterion which requires a fixed OER mentioned in Refs. [8,10,11], the variable setpoint of OER is tracked to obtain the maximum net power by an OER reference governor. This reference governor produces a required reference value of optimal OER which can maximize the net power P_{net}.

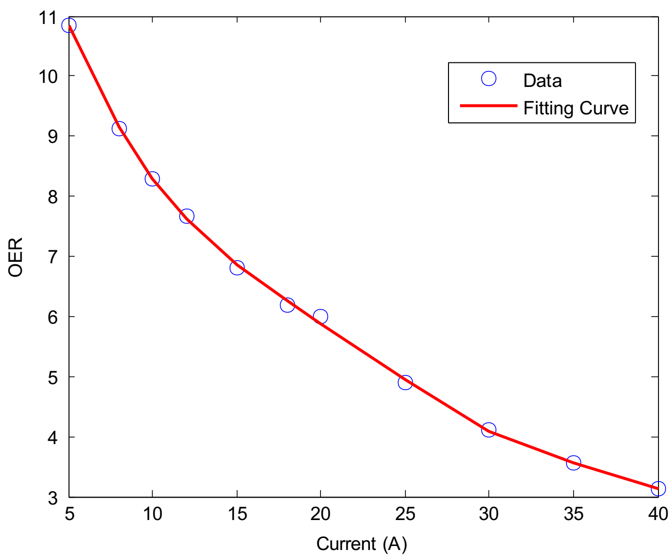

Fig. 4. Fitting result of OER_{op} as a function of I_{net}.

In order to track the optimal OER trajectory, the reference governor is designed by a polynomial fitting method based on an orthogonal matrix Q and an upper triangular matrix R decomposition of Vandermonde matrices (also called a QR decomposition). The fitting result of OER_{op} as a function of I_{net} is shown in Fig. 4 and the equation is expressed as follows

$$OER_{op} = \sum_{k=0}^{6}\left[a_k \cdot (I_{net})^k\right] \tag{16}$$

In this paper, the MNPC strategy is designed based on the IGPC controller and the OER reference governor to keep the OER as close as possible to the optimal objective value. This proposed strategy provides a swift move toward the steady-state value regarding the I_{net} and reduces the transient effects of I_{net} change and any other disturbances and uncertainties which are not considered in the model. The structure of the proposed PEMFC control system is shown in Fig. 5.

4. Results and discussions

In this study, three conditional tests are implemented in order to assess the capability of the proposed strategy to track the variable setpoint of OER, which are common working scenarios in automotive applications of PEMFC. In order to compare the performance of EIA-PSO with other algorithms, the optimization problem of the IGPC is also implemented by using PSO with linear reduction strategy of inertia weight (PSO-w), PSO with constriction factor (PSO-cf) and comprehensive learning particle swarm optimizer (CLPSO) [26–28]. In all experiments, the population size is 15, the maximal iteration number is 20 and the run number is 5. All the algorithms are run on a PC (Core2 CPU 1.86 GHz, 2G RAM) with the same objective function, maximal iteration number and the population size. The preferences of these algorithms are based on the Ref. [30].

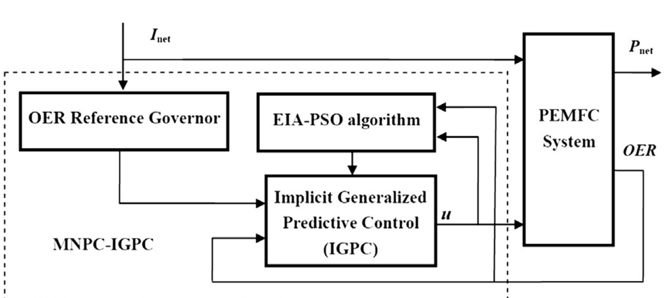

Fig. 5. Structure of PEMFC control system.

In Table 1, J is the best value in all objective function values over 5 runs, Mean is the average objective function value over 5 runs and Std is the standard deviation. A small Std indicates that the data points tend to be very close to Mean, whereas big Std indicates that the data are spread out over a large range of values. In order to determine whether the results obtained by EIA-PSO are statistically different from the results generated by other algorithms, the T-tests which are any statistical hypothesis test and follow a Student's T distribution are conducted. A H value represents the T-tests decision for the null hypothesis. The H value of one indicates that the performances of the two algorithms are statistically different with 95% certainty, whereas the H value of zero implies that the performances are not statistically different. The CI is confidence interval. Table 1 indicates that EIA-PSO has the smallest J, Std, and Mean than all the listed other algorithms, all the H values are equal to one, and all the CI are less than zero and do not contain zero. Hence, the conclusion can be drawn that EIA-PSO is significantly better and statistically more robust than all the other listed algorithms in terms of global search capacity and local search precision.

In the time-domain, the simulation comparisons between the MNPC–IGPC and the PID control method are carried out as shown in Fig. 6. The required reference signal which must send to the PID controller is produced by the proposed OER reference governor. In order to verify the control performance, the step series of I_{net} performed from 11 A to 2 0A as the large disturbances are shown in Fig. 6(a). In Fig. 6(b), the OER_{op} ranges from 5.88 to 7.93 during 50 s, seeking the best trajectory for optimized PEMFC system operation.

In first conditional test defined as nominal condition (no noise or time delay), both the MNPC–IGPC and PID control are successful in keeping the optimal setpoint of OER and rejects the disturbances as shown in Fig. 6(b). However, the response of OER produced by PID control has much more oscillation and the setting time of PID control is much bigger. The response of OER achieved by the MNPC–IGPC has less oscillation, setting time and steady-state error.

In second conditional test defined as time delay condition, the time delay module is added into the OER reference governor output and the delay time is 0.2 s. In Fig. 6(c), the better tracking capability and disturbance rejection capability of MNPC–IGPC are realized than the PID control according to the previous net current profile. The oscillation, setting time and steady-state error of PID control are bigger due to the existence of the time delay.

In third conditional test defined as real condition, the environmental noise signal which has mean value 0 and variance 20 is added into the system input and the measurement noise signal which has mean value 0 and variance 0.5 is also added into the

Table 1
Results of each algorithm.

Criterion	Algorithms			
	PSO-w	CLPSO	PSO-cf	EIA-PSO
J	3.26	3.41	3.32	3.20
Mean	3.37	3.50	3.43	3.28
Std	0.31	0.39	0.35	0.26
H	1	1	1	-
CI	[-6.2×10^{-1}, -8.8×10^{-2}]	[-2.4×10^{-1}, -1.3×10^{-2}]	[-5.5×10^{-1}, -4.7×10^{-2}]	-

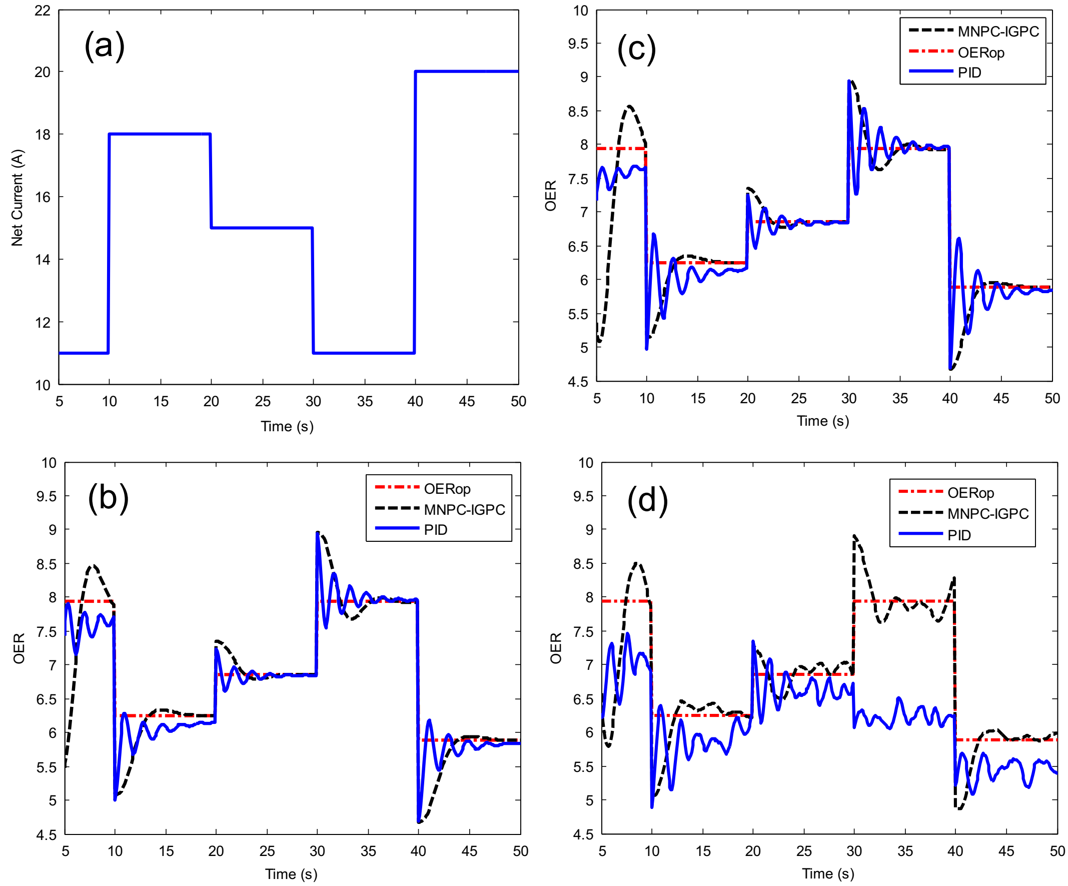

Fig. 6. (a) Net current profile; (b) response curves of OER in first condition; (c) response curves of OER in second condition; and (d) response curves of OER in third condition.

controller input based on the second conditional test. In Fig. 6(d), the MNPC–IGPC can keep the optimal setpoint of OER with less steady-state error under this perturbed condition. The response of OER is far from the optimal setpoint of OER by the PID control so that the tracking capability cannot be achieved. Hence, the better tracking capability and disturbance and noise rejection capability of MNPC–IGPC are reflected than the PID control in this perturbation system.

The experimental comparison of the delivered net power between the MNPC–IGPC and the Nexa Power Module internal control system is carried out as shown in Fig. 7. This commercial internal control system of Nexa Power Module has its own control strategy. The step series of I_{net} performed from 11 A to 20 A as the large disturbances. This net current profile is the same as shown in Fig. 6(a). The MNPC–IGPC delivers greater net power than the Nexa control. The maximal difference of output net power between the MNPC–IGPC and the Nexa control is 30 W approximately. Therefore, the proposed MNPC–IGPC can guarantee optimal OER and the maximum net power.

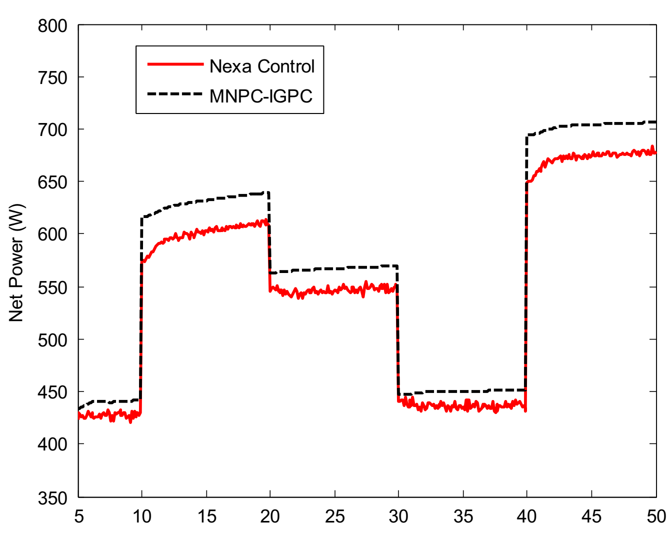

Fig. 7. Comparison of the delivered net power between the MNPC–IGPC and the Nexa control.

5. Conclusions

In this paper, the maximum net power characterization of PEMFC system which has been implemented in MATLAB/SIMULINK environment is developed. The maximum net power profile determines the optimal OER trajectory. This paper proposes to follow this optimal OER trajectory in order to supply the maximum net power and smooth behavior of OER. A MNPC strategy based on the IGPC and the reference governor is proposed to keep the OER as close as possible to the optimal objective value. The IGPC based on the EIA-PSO algorithm which improves inherent drawbacks of the PSO is developed to solve the predictive control law in the rolling optimization process. This method can avoid solving the Diophantine equation online, reduce computational complexity and directly identify the parameters of predictive control law by the characteristics of the parallel predictors. The OER reference

governor is designed by a polynomial fitting method based on QR decomposition of Vandermonde matrices. The proposed strategy allows an efficient and safe OER control while maximizing the net power of PEMFC system. The simulations of three conditional tests are carried out and the results demonstrate that the proposed strategy can track the optimal OER trajectory, reduce the parasitic power and maximize the output net power. In addition, it is proved that the EIA-PSO algorithm outperforms various versions of the PSO algorithm on this optimization problem. Furthermore, the comprehensive comparisons based on three conditional tests verify that the MNPC–IGPC has better transient behavior and robust performance in the presence of large disturbances, time delay and various noises. The experimental comparison with the commercial Nexa Power Module internal control system also testifies the validity and superiority of the MNPC–IGPC for the maximum net power. Therefore, this proposed strategy will give a new approach for the design of advanced PEMFC net power control system.

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